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6.1 Simple Hypothesis

In scientific activities, much attention is devoted to answering questions about the validity of theories or hypotheses concerning physical phenomena.

- Is a new drug effective?
- Does a lot of manufactured items contain an excessive number of defectives?
- Is the mean lifetime of a component at least some specified amount?

The term **hypotheses testing** will refer to the process of trying to decide the truth or falsity of such hypotheses on the basis of experimental evidence.

**Definition 1.** If  $X \sim f(x; \theta)$ , a statistical hypothesis is a statement about the distribution of  $X$ . If the hypothesis completely specifies  $f(x; \theta)$ , then it is referred to as a **simple hypothesis**; otherwise it is called **composite**.

**Example 1.**

A theory proposes that the yield of a certain chemical reaction is normally distributed  $X \sim N(\mu, 16)$ . Past experience indicates that  $\mu = 10$  if a certain mineral is not present, and  $\mu = 11$  if the mineral is present. Our experiment would be to take a random sample of size  $n$ . On the basis of that sample, state the null hypothesis and the alternative hypothesis.

**Definition 2.** The **critical region** for a test of hypotheses is the subset of the sample space that corresponds to rejecting the null hypothesis.

In the normal distribution example,  $\bar{X}$  is a sufficient statistic for  $\mu$ , so we may conveniently express the critical region directly in terms of  $\bar{X}$ , and we will refer to  $\bar{X}$  as the test statistic. Because  $\mu_1 > \mu_0$  natural form for the critical region in this problem is to let  $C = \{(x_1, \dots, x_n) | \bar{x} \geq c\}$  for some appropriate constant  $c$ . That is, we will reject  $H_0$  if  $\bar{x} \geq c$ , and we will not reject  $H_0$  if  $\bar{x} < c$ .

There are two possible errors we may make under this procedure. We might reject  $H_0$  when  $H_0$  is true, or we might fail to reject  $H_0$  when  $H_0$  is false. These errors are referred to as follows:

- Type I error: Reject a true  $H_0$ .
- Type II error: Fail to reject a false  $H_0$ .

We hope to choose a test statistic and a critical region so that we would have a small probability of making these two errors. We will adopt the following notations for these error probabilities:

- $P[\text{Type I error}] = P[TI] = \alpha$
- $P[\text{Type II error}] = P[TII] = \beta$ .

**Definition 3.** For a simple null hypothesis,  $H_0$ , the probability of rejecting a true  $H_0$ ,  $\alpha = P[TI]$ , is referred to as the **significance level** of the test. For a composite null hypothesis,  $H_0$ , the size of the test (or size of the critical region) is the maximum probability of rejecting  $H_0$  when  $H_0$  is true (maximized over the values of the parameter under  $H_0$ ).

**Definition 4.** The **power function**,  $\pi(\theta)$ , of a test of  $H_0$  is the probability of rejecting  $H_0$  when the true value of the parameter is  $\theta$ .

**Example 2.**

Suppose  $X_i \sim N(\mu, 16)$ ,  $n = 25$ ,  $H_0 : \mu = 10$ ,  $H_1 : \mu = 11$ ,  $\alpha = 5\%$ . Find the probability of Type I and Type II errors,  $\alpha$  and  $\beta$ ;

- (a) if the critical region is  $\bar{x} \geq 11.316$ ,
- (b) if the critical region is  $C_1 = \{(x_1, \dots, x_n | 10 < \bar{x} < 10.1006)\}$ .

**Example 3.**

For Jones’ political poll,  $n = 15$  voters were sampled. We wish to test  $H_0 : p = .5$  against the alternative,  $H_1 : p < .5$ . The test statistic is  $X$ , the number of sampled voters favoring Jones. Calculate  $\alpha$  if we select  $\{x \leq 2\}$  as the rejection region.

**Example 4.**

Refer to Example 3. Is our test equally good in protecting us from concluding that Jones is a winner if in fact he will lose? Suppose that he will receive 30% of the votes ( $p = .3$ ). What is the probability  $\beta$  that the sample will erroneously lead us to conclude that  $H_0$  is true and that Jones is going to win?

<div data-bbox="73 10 531 46" data-label="Section-Header"> <h2>6.2 Composite Hypotheses</h2> </div> <div data-bbox="73 69 256 107" data-label="Section-Header"> <h3>Example 5.</h3> </div> <div data-bbox="73 107 714 384" data-label="Text"> <p>Again, we assume that <math>X \sim N(\mu, \sigma^2)</math>, where <math>\sigma^2</math> is known, and we wish to test <math>H_0 : \mu = \mu_0</math> against the composite alternative <math>H_1 : \mu &gt; \mu_0</math>. For any alternative <math>\mu_1 &gt; \mu_0</math>, the critical region should be located on the right hand tail. The critical value <math>c</math> did not depend on the value of <math>\mu_1</math>. For a test at significance level <math>\alpha</math></p> </div> <div data-bbox="73 401 482 438" data-label="Text"> <p>(a) What is the critical region?</p> </div> <div data-bbox="73 892 714 913" data-label="Page-Footer"> <div>MEME15203 STATISTICAL INFERENCE©DR YONG CHIN KHIAN</div> <div>202501</div> </div>	<div data-bbox="862 10 1198 46" data-label="Text"> <p>(b) The power function is</p> </div> <div data-bbox="862 892 1503 913" data-label="Page-Footer"> <div>MEME15203 STATISTICAL INFERENCE©DR YONG CHIN KHIAN</div> <div>202501</div> </div>
<div data-bbox="220 1066 714 1096" data-label="Page-Header"> <div>Chapter 6 Tests of Hypotheses</div> <div>11</div> </div> <div data-bbox="73 1125 462 1218" data-label="List-Group"> <p>(c) What is <math>\pi(\mu_0)</math>?</p> <p>(d) What is <math>\pi(\mu)</math> for <math>\mu &gt; \mu_0</math>?</p> </div> <div data-bbox="73 2005 714 2026" data-label="Page-Footer"> <div>MEME15203 STATISTICAL INFERENCE©DR YONG CHIN KHIAN</div> <div>202501</div> </div>	<div data-bbox="1008 1066 1503 1096" data-label="Page-Header"> <div>Chapter 6 Tests of Hypotheses</div> <div>12</div> </div> <div data-bbox="862 1125 1503 1738" data-label="Text"> <p>We also may consider a composite null hypothesis. Suppose that we wish to test <math>H_0 : \mu \leq \mu_0</math> against <math>H_1 : \mu &gt; \mu_0</math> and we reject <math>H_0</math> if <math>z_0 = \frac{\bar{x}-\mu_0}{\sigma/\sqrt{n}}</math> is satisfied. This is still a size <math>\alpha</math> test for the composite null hypothesis. The probability of rejecting <math>H_0</math> for any <math>\mu \leq \mu_0</math> is <math>\pi(\mu)</math>, and <math>\pi(\mu) \leq \pi(\mu_0) = \alpha</math> for <math>\mu \leq \mu_0</math>, and thus the size is <math>\max_{\mu \leq \mu_0} \pi(\mu) = \alpha</math>. That is, if the critical region is chosen to have size at <math>\mu_0</math>. then the Type I error will be less than <math>\alpha</math> for any <math>\mu &lt; \mu_0</math>, so the original critical region still is appropriate here. Thus, the a level tests developed for simple null hypotheses often are applicable to the more realistic composite hypotheses, and P[TI] will be no worse than <math>\alpha</math>.</p> <div data-bbox="862 2005 1503 2026" data-label="Page-Footer"> <div>MEME15203 STATISTICAL INFERENCE©DR YONG CHIN KHIAN</div> <div>202501</div> </div> </div>

### Example 6.

Let  $X_1, \dots, X_{25}$  be a random sample of size  $n$  from an exponential distribution,  $X_i \sim \text{Exp}(\eta, \theta = 40)$ . A test of  $H_0 : \eta = 10.95$  versus  $H_1 : \eta = 16.04$  is desired, based on  $X_{1:n}$ . A critical region of size  $\alpha = 0.04$  is of the form  $\{x_{1:n} \geq c\}$ .

- (a) Find  $c$ .
- (b) Determine the power of the test under  $H_1$ .

### 6.3 P-Value

There is not always general agreement about how small  $\alpha$  should be for rejection of  $H_0$  to constitute strong evidence in support of  $H_1$ . Experimenter 1 may consider  $\alpha = 0.05$  sufficiently small, while experimenter 2 insists on using  $\alpha = 0.01$ . Thus, it would be possible for experimenter 1 to reject when experimenter 2 fails to reject, based on the same data. If the experimenters agree to use the same test statistic, then this problem may be overcome by reporting the results of the experiment in terms of the observed size or p-value of the test, which is defined as the smallest size  $\alpha$  at which  $H_0$  can be rejected, based on the observed value of the test statistic.

**Definition 5.** If  $W$  is a test statistic, the p-value, or attained significance level, is the smallest level of significance  $\alpha$  for which the observed data indicate that the null hypothesis should be rejected.

### Example 7.

Refer to example 4, where  $n = 15$  voters were sampled. If we wish to test  $H_0 : p = .5$  versus  $H_1 : p < .5$ , using  $X =$  the number of voters favoring Jones as our test statistic, what is the p-value if  $X = 3$ ?

### 6.4 Most Powerful Tests

Let  $X_1, \dots, X_n$  have joint pdf  $f(x_1, \dots, x_n; \theta)$  and consider a critical region  $C$ . The notation for the power function corresponding to  $C$  is

$$\pi_C(\theta) = P[X_1, \dots, X_n \in C | \theta]$$

**Definition 6.** A test of  $H_0 : \theta = \theta_0$  versus  $H_1 : \theta = \theta_1$  based on a critical region  $C^*$  is said to be a most powerful test of size  $\alpha$  if

1.  $\pi_{C^*}(\theta_0) = \alpha$ , and
2.  $\pi_{C^*}(\theta_1) \geq \pi_C(\theta_1)$  for any other critical region  $C$  of size  $\alpha$  [that is,  $\pi_C(\theta_0) = \alpha$ ]

Such a critical region,  $C^*$ , is called a most powerful critical region of size  $\alpha$ .





## 6.5 Uniformly Most Powerful Tests

**Definition 7.** Let  $X_1, \dots, X_n$  have joint pdf  $f(x_1, \dots, x_n; \theta)$  for  $\theta \in \Omega$ , and consider hypotheses of the form  $H_0 : \theta \in \Omega_0$  versus  $H_1 : \theta \in \Omega - \Omega_0$  where  $\Omega_0$  is a subset of  $\Omega$ . A critical region  $C^*$ , and the associated test are said to be uniformly most powerful (UMP) of size  $\alpha$  if

$$\max_{\theta \in \Omega} \pi_{C^*}(\theta) = \alpha$$

and

$$\pi_{C^*}(\theta) \geq \pi_C(\theta)$$

for all  $\theta \in \Omega - \Omega_0$  and all critical regions  $C$  of size  $\alpha$ .

A UMP test often exists in the case of a one-sided composite alternative, and a possible technique for determining a UMP test is first to derive the Neyman- Pearson test for a particular alternative value and then show that the test does not depend on the specific alternative value.

**Example 14.** Suppose that  $X_1, X_2, \dots, X_n$  constitute a random sample from a normal distribution with known mean  $\mu$  and unknown variance  $\sigma^2$ . Find the most powerful  $\alpha$ -level test of  $H_0 : \sigma^2 = \sigma_0^2$  versus  $H_1 : \sigma^2 = \sigma_1^2$ , where  $\sigma_1^2 > \sigma_0^2$ . Show that this test is equivalent to a  $\chi^2$  test. Is the test uniformly most powerful for  $H_1 : \sigma^2 > \sigma_0^2$ ?

**Example 15.** Refer to example 10, is the test uniformly most powerful for the alternative  $\theta > \theta_0$ ?

**Definition 8.** A joint pdf  $f(\mathbf{x}; \theta)$  is said to have a monotone likelihood ratio (MLR) in the statistic  $T = t(\mathbf{X})$  if for any two values of the parameter,  $\theta_1 < \theta_2$ , the ratio  $f(\mathbf{x}; \theta_2)/f(\mathbf{x}; \theta_1)$  depends on  $\mathbf{x}$  only through the function  $t(\mathbf{x})$ , and this ratio is a nondecreasing function of  $t(\mathbf{x})$ .

Notice that the MLR property also will hold for any increasing function of  $t(\mathbf{x})$ .

**Example 16.** Consider a random sample of size  $n$  from an exponential distribution,  $X \sim EXP(\theta)$ . Show that  $f(\mathbf{x}; \theta)$  has the MLR property in the statistic  $T = \sum X$ .

The MLR property is useful in deriving UMP tests.

**Theorem 2.** If a joint pdf  $f(\mathbf{x}; \theta)$  has a monotone likelihood ratio in the statistic  $T = t(\mathbf{x})$  then a UMP test of size for  $H_0 : \theta \leq \theta_0$  versus  $H_1 : \theta > \theta_0$  is to reject  $H_0$  if  $t(\mathbf{x}) > k$ , where  $P[t(\mathbf{X}) \geq k | \theta_0] = \alpha$ .

The dual problem of testing  $H_0 : \theta \geq \theta_0$  versus  $H_1 : \theta < \theta_0$  also can be handled by the MLR approach, but the inequalities in the above Theorem should be reversed. Also, if the ratio is a nonincreasing function of  $t(\mathbf{x})$ , then  $H_0$  of the theorem can be rejected with the inequalities in  $t(\mathbf{x})$  reversed.

**Example 17.**

Let  $X_1, \dots, X_n$  denote the incomes of  $n$  persons chosen at random from a certain population. Suppose that each  $X_i$  has the Pareto density

$$f(x, \alpha) = \frac{\alpha 500^\alpha}{x^{\alpha+1}}, x > 500$$

where  $\alpha > 1$ .

- (a) Express mean income  $\mu$  in terms of  $\alpha$ .
- (b) Find the Uniformly Most Powerful test for testing  $H_0 : \mu = \mu_0$  versus  $H_1 : \mu > \mu_0$ .

**Theorem 3.** Suppose that  $X_1, \dots, X_n$  have joint pdf of the form  $f(\mathbf{x}; \theta) = c(\theta)h(\mathbf{x})exp[q(\theta)t(\mathbf{x})]$  where  $q(\theta)$  is an increasing function of  $\theta$ .

- 1. A UMP test of size for  $H_0 : \theta \leq \theta_0$  versus  $H_1 : \theta > \theta_0$  is to reject  $H_0$  if  $t(\mathbf{x}) \geq k$ , where  $P[t(\mathbf{X}) \geq k | \theta] = \alpha$ .
- 2. A UMP test of size for  $H_0 : \theta \geq \theta_0$  versus  $H_1 : \theta < \theta_0$  is to reject  $H_0$  if  $t(\mathbf{x}) \leq k$ , where  $P[t(\mathbf{X}) \leq k | \theta] = \alpha$ .



**Example 18.**

Let  $X_1, \dots, X_4$  denote a random sample from a gamma distribution,  $X_i \sim GAM(2, \theta)$ . Derive a UMP size 0.05 test of  $H_0 : \theta \leq 1.0$  versus  $H_1 : \theta > 1.0$ , then find the power of this test when  $\theta = 2$ .

**6.6 Generalized Likelihood Ratio Tests**

**Definition 9.** Let  $\mathbf{X} = (X_1, \dots, X_n)$  where  $X_1, \dots, X_n$  have joint pdf  $f(\mathbf{x}; \boldsymbol{\theta})$  for  $\boldsymbol{\theta} \in \Omega$  and consider the hypothesis  $H_0 : \boldsymbol{\theta} \in \Omega$  versus  $H_1 : \boldsymbol{\theta} \in \Omega - \Omega_0$ . The **generalized likelihood ratio** (GLR) is defined by

$$\lambda(\mathbf{x}) = \frac{\max_{\boldsymbol{\theta} \in \Omega_0} f(\mathbf{x}; \boldsymbol{\theta})}{\max_{\boldsymbol{\theta} \in \Omega} f(\mathbf{x}; \boldsymbol{\theta})} = \frac{f(\mathbf{x}; \hat{\boldsymbol{\theta}}_0)}{f(\mathbf{x}; \hat{\boldsymbol{\theta}})}$$

where  $\hat{\boldsymbol{\theta}}$  denotes the usual MLE of  $\boldsymbol{\theta}$ , and  $\hat{\boldsymbol{\theta}}_0$  denotes the MLE under the restriction that  $H_0$  is true.

In other words,  $\hat{\boldsymbol{\theta}}$  and  $\hat{\boldsymbol{\theta}}_0$  are obtained by maximizing  $f(\mathbf{x}; \boldsymbol{\theta})$  over  $\Omega$  and  $\Omega_0$ , respectively. The generalized likelihood ratio test is to reject  $H_0$  if  $\lambda(x) \leq k$ , where  $k$  is chosen to provide a size  $\alpha$  test.

We see that  $\lambda(\mathbf{X})$  is a valid test statistic that is not a function of unknown parameters; in many cases the distribution of  $\lambda(\mathbf{X})$  is free of parameters, and the exact critical value  $k$  can be determined. In some cases the distribution of  $\lambda(\mathbf{X})$  under  $H_0$  depends on unknown parameters, and an exact size critical region cannot be determined. If regularity conditions hold, which ensure that the MLEs are asymptotically normally distributed, then it can be shown that the asymptotic distribution of  $\lambda(\mathbf{X})$  is free of parameters, and an approximate size  $\alpha$  test will be available for large  $n$ . In particular, if  $\mathbf{X} \sim f(\mathbf{x}; \theta_1, \dots, \theta_k)$ , then under  $H_0 : (\theta_1, \dots, \theta_r) = (\theta_{10}, \dots, \theta_{r0}), r < k$ , approximately, for large  $n$ ,

$$-2 \ln \lambda(\mathbf{X}) \sim \chi^2(r)$$

Thus an approximate size test is to reject  $H_0$  if

$$-2 \ln \lambda(\mathbf{X}) \geq \chi^2_{1-\alpha}(r)$$

**Example 19.**

Suppose that  $X \sim N(\mu, \sigma^2)$  where  $\sigma^2$  is known and we wish to test  $H_0 : \mu = \mu_0$  versus  $H_1 : \mu \neq \mu_0$ , derive the GLR test.

**Example 20.**

Suppose that  $X \sim N(\mu, \sigma^2)$  where  $\mu$  and  $\sigma^2$  are both unknown and we wish to test  $H_0 : \mu = \mu_0$  against  $H_1 : \mu \neq \mu_0$ , derive the GLR test.

**Example 21.**

Let  $X_1, \dots, X_n$  be a random sample from an exponential distribution,  $X_i \sim EXP(\theta)$ . Derive the generalized likelihood ratio (GLR) test of  $\theta = \theta_0$  versus  $\theta \neq \theta_0$ . Determine and approximate critical value for size  $\alpha$  using the large-sample chi-square approximation.

**Example 22.**

Let  $X_1, \dots, X_n$  be a random sample from an exponential distribution,  $X_i \sim EXP(\theta)$ . Derive the generalized likelihood ratio (GLR) test of  $H_0 : \theta = \theta_0$  versus  $H_1 : \theta > \theta_0$ .

**Example 23.**

Let  $X_1, X_2, \dots, X_k$  denote a random sample from a gamma distribution  $X_i \sim GAM(\alpha_1 = 2, \theta_1)$  and let  $Y_1, Y_2, \dots, Y_l$  denote an independent random sample from a gamma distribution  $Y_i \sim GAM(\alpha_2 = 2, \theta_2)$ .

- Find the likelihood ratio criterion for testing  $H_0 : \theta_1 = \theta_2$  versus  $H_1 : \theta_1 \neq \theta_2$
- Show that the test in part (a) can be based on the statistic

$$T = \frac{\sum X_i}{\sum X_i + \sum Y_i}.$$

6.7 Bayesian Tests of Hypotheses

Tests of hypotheses can also be approached from a Bayesian perspective. When testing  $H_0 : \theta \in \Omega_0$  versus  $H_1 : \theta \in \Omega_1$ . We compute the posterior probabilities  $P^*(\theta \in \Omega_0)$  and  $P^*(\theta \in \Omega_1)$  and reject the hypothesis with lower posterior probability. That is for testing  $H_0 : \theta \in \Omega_0$  versus  $H_1 : \theta \in \Omega_1$ , we reject  $H_0$  if  $P^*(\theta \in \Omega_0) < P^*(\theta \in \Omega_1)$ .

Example 24.

Suppose that  $X$  has pdf  $f(x|\theta) = 2\theta(1-2x)+2x$  on  $[0, 1]$ . A Bayesian wants to test  $H_0 : \theta \leq 0.62$  versus  $H_1 : \theta > 0.62$ . If the Bayesian prior distribution is  $U[0, 1]$ , what is the person’s test?

Example 25.

If  $X \sim POI(\lambda)$  and a Bayesian uses a prior for  $\lambda$  that is Exponential with mean 1, what is the Bayes test of  $H_0 : \lambda \leq 2$  versus  $H_1 : \lambda > 2$ ?